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Implementing a Convolutional Neural Network with Adam Optimizer for Pneumonia Detection Through Chest X-ray Imaging

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Abstract

Pneumonia occurs frequently and can be life-threatening all over the world, mainly in locations where radiologists are hard to find. Even though chest X-ray imaging is widely used, correctly and promptly interpreting it is difficult due to human error and inadequate resources. It aims to overcome the problem of limited, reliable resources for advanced radiology by designing and evaluating a CNN model that can distinguish chest X-rays with and without pneumonia. To increase the usability of the model, the chest X-ray images were processed by being resized to a size of 224×224×3 and then enlarged through random rotation, flipping, and translation. The data was split so that 80 percent went to the training set and 20 percent to the testing set. Several layers were built into the custom CNN for overfitting prevention, such as convolution, pooling, batch normalization, ReLU, and dropout. For 20 epochs, I used Adam as the optimizer and set the mini-batch size to 32 and the learning rate to 1e-4. The model correctly distinguished between pneumonia and normal lung cases over 95% of the time. We found that the model was robust thanks to the confusion matrix and a close study of sample images after prediction. Microwave-based deep learning is introduced in this paper, which demonstrates strong accuracy in detecting pneumonia and makes it possible to use the tool as an automatic device for medical and remote healthcare screening.

Keywords: Convolutional Neural Network (CNN), Chest X-rays, Accuracy Alongside Precision Recall, ReLU, Confusion Matrix Evaluation

Introduction

The respiratory ailment known as pneumonia is one of the most common and potentially fatal respiratory illnesses in the world. It is responsible for a large amount of morbidity and mortality across a wide range of people. Figure 1 illustrates the prevalence of microbial aetiologies of community-acquired pneumonia (CAP) in the USA and Europe (Lim et al., 2021). It poses a direct threat to vulnerable populations, including infants, older people, and people with compromised immune systems, among other susceptible groups (Mateo et al., 2021). According to the World Health Organization, pneumonia is the biggest cause of death among children under the age of five and is responsible for millions of hospitalizations each year (Chakrabarty et al., 2018). In nations with low and intermediate incomes, where healthcare resources and prompt access to medical specialists are frequently severely constrained, the impact of the disease is even more pronounced than in those with higher incomes (Hussin Adam Khatir et al., 2022). Chest X-ray imaging is a basic and cost-effective method for detecting pneumonia; yet, the appropriate interpretation of these pictures continues to be a challenge, even though it is always available (Hasan et al., 2024).

Experience is necessary in radiology because pneumonia symptoms may be hard to tell apart from those of other problems relating to breathing or other parts of the body. In addition, the accuracy in diagnosing patients can be lowered by human factors such as tiredness, the way individuals interpret images, and differences in the way mistakes are handled by radiologists. It becomes even worse when there are too many cases for a few trained specialists to interpret (Hasan et al., 2024). Because of this, using AI and deep learning tools has proved to be an important advance in medical image analysis. CNNs are effective at spotting and categorizing complex images, so they have shown outstanding outcomes in activities such as tumor detection, analyzing fractures, and identifying issues with the lungs. Because they can process a lot of labeled information well and are accurate at finding signs of pneumonia, they may help physicians detect this condition at an early stage. Using AI, machines can process lab tests more rapidly, prevent mistakes during diagnosis, and help regions without many specialists (Rehman et al., 2023). Even so, there are still difficulties in making certain that these machine learning models work well in different patient settings and can be proven reliable. For this reason, we should investigate what research is being done in AI-based recognition of pneumonia. Knowing the methods, results, and weaknesses of prior studies allows us to understand what should be done next. Therefore, the next section looks closely at what has been done in this domain, which provides a basis for our study and emphasizes the key things it aims to improve (Rahman, 2020).

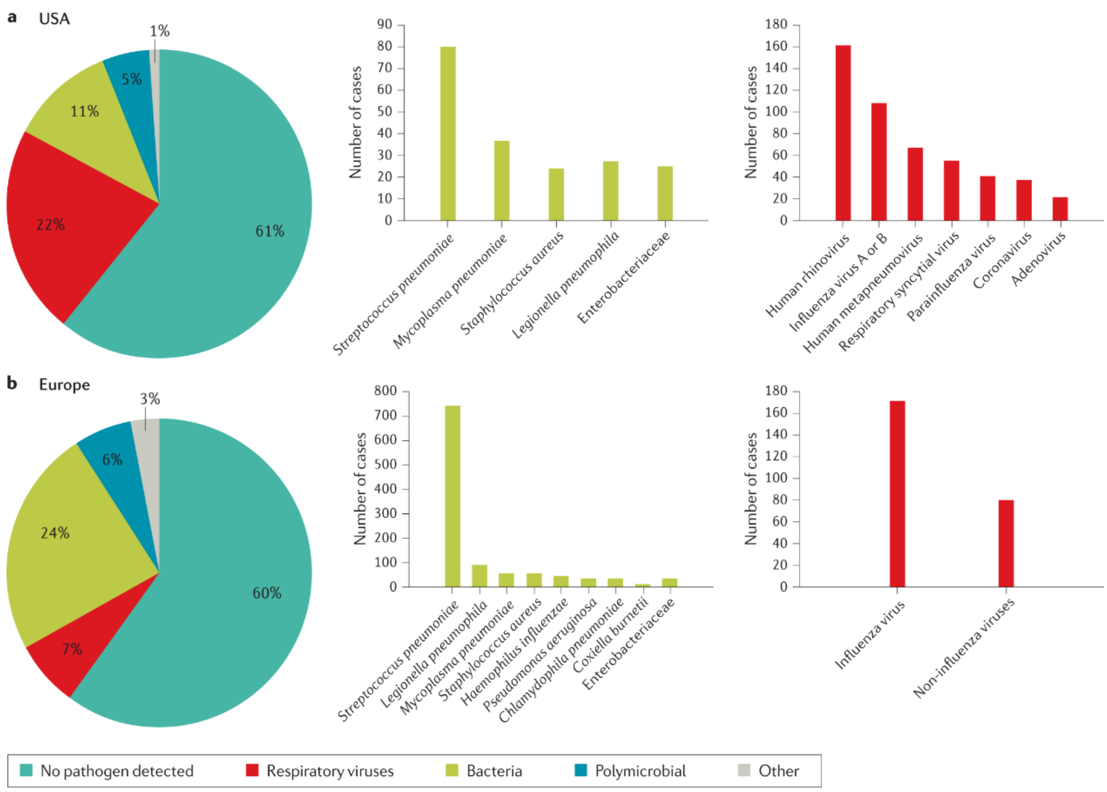

Figure 1. Prevalence of microbial aetiologies of CAP in the USA and Europe

Literature Review

In the last several years, more attention has been given to using deep learning for detecting pneumonia from X-ray pictures in the medical imaging area. Researchers have examined the capabilities, accuracy, and relevance of AI to assist radiologists in detecting pneumonia early. Khan et al. (2021) reviewed previous literature to investigate how chest X-rays can be interpreted by machines for the detection of pneumonia. They discussed the development of various machine learning and deep learning techniques, particularly convolutional neural networks (CNNs), and evaluated their performance and robustness (Khan et al., 2021; Lim et al., 2021). Even so, the study focused on the difficulties caused by unbalanced datasets, the ability of models to work across different contexts, and model interpretability. They further examined recent progress in deep learning for pneumonia prediction. They mentioned that CNN-based models were more accurate yet highlighted that their use in healthcare is not widespread because studies often use different preprocessing methods and have uneven data quality. They suggested a new technique in which African Buffalo Optimization and CNNs work together to better identify and classify pneumonia in X-rays. Transformer-based models were able to achieve better results than conventional CNN models (Mateo et al., 2021). At the same time, it was questioned whether cloud-based hybrid learning could be effective or practical in a clinical setting (Mateo et al., 2021). Rehman et al. (2023) examined multiple deep learning models for detecting chest disease and mentioned that top-performing models are often trained on very large datasets. They mentioned that transfer learning and ensembles are necessary, noting that many mistakes may still arise because of substantial overfitting and a lack of adequate data (Rehman et al., 2023). In their study, Chen et al. (2024) included the use of machine learning for diagnosing COVID-19-related pneumonia in CT images, noting that combining radiomics with AI can make diagnoses more accurate.

Still, since these approaches rely on CT scans, they are not appropriate for screening general pneumonia in regions where X-ray equipment is the main option (Chen et al., 2024). Recently, Goel and Sobti (2025) designed a deep cognitive learning structure with CNNs to enhance the detection of pneumonia. The model accurately predicted outcomes but was not adequately tested on people outside the group from which it was trained (Goel & Sobti, 2025). According to Alalwan et al. (2024) and Rehman et al. (2023), Figure 2 shows a comparison of the receiver operating characteristic (ROC) curves for normal pneumonia (A), normal, bacterial, and viral pneumonia (B), and bacterial and viral pneumonia (C) classification using CNN-based models. Besides, many research works barely address model performance properly, mainly through the metrics of accuracy, precision, recall, F1-score, ROC-AUC, and analysis of entropy levels in texts. Additionally, in another study (Khan et al., 2021), Figure 3 shows the class activation mapping (CAM): (A) Normal, (B) Bacterial Pneumonia, and (C) Viral Pneumonia using CNN, and it demonstrated its accuracy. While this domain has advanced, some critical gaps persist.

Most of the reviewed models use complex methods that are difficult to implement in real-world settings, or they are evaluated using data that are not well balanced. This article aims to address these issues by designing a highly efficient CNN and training it on a preprocessed and extended collection of chest X-ray images. The purpose is to achieve good performance and efficiency, including the use of entropy analysis to provide further insights into how a model behaves. As a result, the research team hopes to provide a solution for pneumonia detection that can work in many places with limited resources.

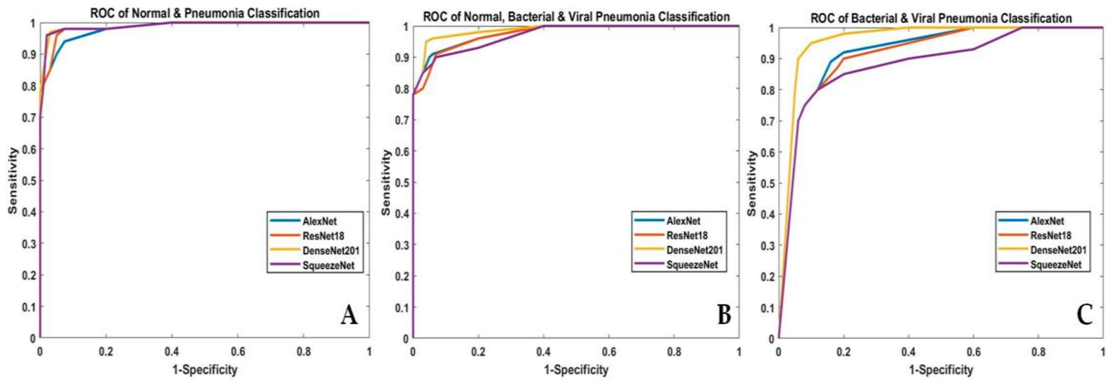

Figure 2. Comparison of the receiver operating characteristic (ROC) curves for normal pneumonia (A), normal, bacterial, and viral pneumonia (B), and bacterial and viral pneumonia (C) classification using CNN-based models proposed by Alalwan et al. (2024) and Khan et al. (2021)

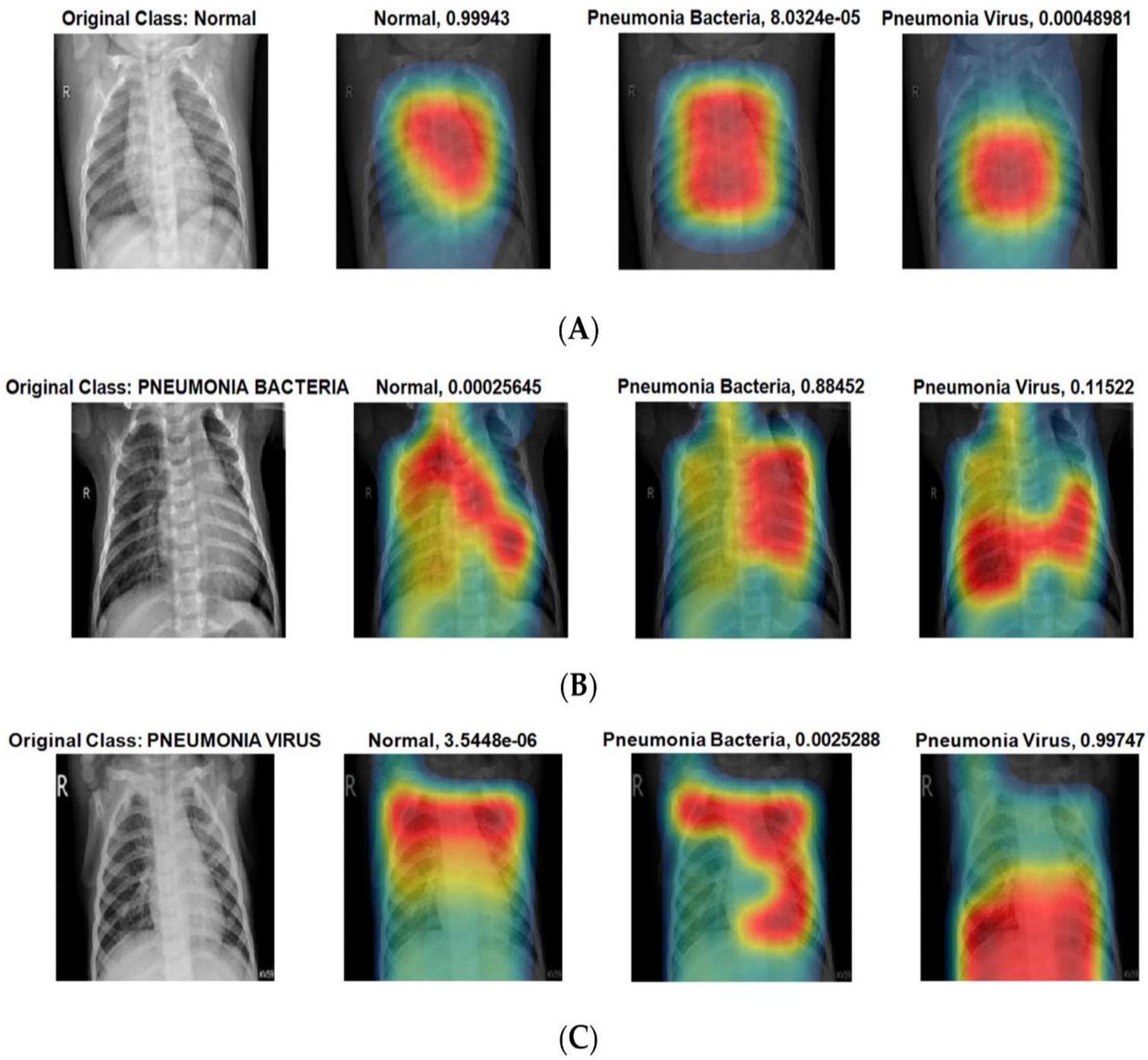

Figure 3. Class Activation Mapping (CAM); (A) Normal, (B) Bacterial Pneumonia, and (C) Viral Pneumonia

Table 1. The performance of classification results with different approaches in previous studies

Study	Dataset	Oversampling Technique	Models Evaluated	Best Model Performance	Key Findings
Chen et al. (2024)	UCI Census	None	Gradient Boosting, Random Forest, SVM, Naïve Bayes, Decision Tree	Gradient Boosting: AUC 0.90	Gradient Boosting outperformed other models without oversampling techniques.
Goel et al. (2025)	Adult Income	None	Logistic Regression, Decision Tree, SVM, k-NN	Accuracy: ~86%	Demonstrated baseline performances without addressing class imbalance.
Alsharif et al. (2021)	Adult Income	None	XGBoost, Random Forest, SVM	XGBoost: Accuracy 87.5%	XGBoost achieved higher accuracy than other models without oversampling.

Methodology

This study employed four sequences that worked in tandem to develop, train, and assess a deep learning system for identifying chest X-ray images as either NORMAL or PNEUMONIA. There are several stages involved; the following (See Figure 4):

- Data Preparation
- Data Augmentation
- Model Design
- Evaluation and Testing

Data Preparation

The first step is to gather the raw data and clean it for use in training a CNN.

1. Dataset Description

For this study, the data includes chest X-rays that are classified into two groups.

- NORMAL: Standing for individuals in good health.
- PNEUMONIA: Involving people who are diagnosed with pneumonia (caused by bacteria or viruses).

MATLAB's imageDatastore is used, which assigns labels to each image based on the folder it is in. As a result, the data can be loaded easily and orderly for deep learning processes.

Image Preprocessing

All the images were adjusted to a size of 224 × 224 × 3, since that is the input specification used by CNNs.

Dataset Splitting

To provide balanced and neutral training, the information in the dataset was divided at random into:

- 80 % is assigned to training the model.
- 20% is put aside for testing.

In MATLAB, the function used ensures that each class is present in an equal amount in each part of the dataset. Table 2 shows the description of the parameter used in dataset splitting.

Table 2. Description of the parameters used in dataset splitting of the proposed model

Parameter	Description
Total number of images	5863
Training set (80%)	4690 images
Testing set (20%)	1173 images
Image size	224 × 224 × 3
Classes	NORMAL, PNEUMONIA
Tool used for labeling	ImageDatastore
Splitting method	SplitEachLabel (balanced per class)

Data Augmentation

To improve the model's ability to generalize and prevent overfitting, a series of data augmentation techniques were applied only to the training dataset. Data augmentation artificially increases the diversity of the training data by creating modified versions of the original images (See Table 3). These techniques simulate real-world variations in image orientation, scale, and position, helping the model learn invariant features.

Table 3. Description of the augmentation techniques of the proposed model

Augmentation Technique	Range/Description
Random rotation	±15 degrees
Horizontal reflection	Random flipping across the horizontal axis
Vertical reflection	Random flipping across the vertical axis
Translation (shift)	±10 pixels along X and Y axes

Model Design

A CNN model was made specifically for the task of distinguishing between NORMAL and PNEUMONIA. Various factors were balanced so that both complexity and ability to learn from many types of data were adequate, as presented in Table 4.

Table 4. Network Architecture of the proposed model

Layer Type	Description
Input Layer	Accepts RGB images of size 224 × 224 × 3
Convolution Layer 1	32 filters, followed by Batch Normalization and ReLU activation
Max Pooling Layer 1	Downsamples the feature map
Dropout Layer 1	Dropout rate = 0.3 (prevents overfitting)
Convolution Layer 2	64 filters, followed by BatchNorm and ReLU
Max Pooling Layer 2	Downsamples the feature map
Dropout Layer 2	Dropout rate = 0.4
Convolution Layer 3	128 filters, followed by BatchNorm and ReLU
Max Pooling Layer 3	Downsamples the feature map
Dropout Layer 3	Dropout rate = 0.5
Fully Connected Layer	256 neurons with ReLU activation
Output Layer	2 neurons (representing 2 classes), followed by Softmax activation
Classification Layer	Computes the final classification result

This architecture allows for progressive feature extraction from raw pixel data, capturing low-level to high-level features through the increasing number of convolutional filters as shown in Table 5.

Table 5. CNN Architecture of the proposed model

Layer Name	Function	Parameters
Input Layer	Accept image	224×224×3
Conv Layer 1	Feature extraction	32 filters
Conv Layer 2	Deeper features	64 filters
Conv Layer 3	High-level abstraction	128 filters
Dropout Layers	Regularization	0.3, 0.4, 0.5
Fully Connected Layer	Classification base	256 neurons
Final FC Layer	Binary output	2 neurons
Softmax + Classification	Output layer	2-class softmax

Training and Evaluation

The Adam optimizer was used to train the model, since it performs efficiently with sparse data and noisy training data, as illustrated in Table 6.

Table 6. Training Parameters of the proposed model

Parameter	Value
Optimizer	Adam
Mini-batch size	32
Number of epochs	20
Initial learning rate	1e-4 (0.0001)
Validation frequency	Every 10 iterations
Validation dataset	Augmented version of test set

MATLAB displayed both the accuracy and loss curves during the model's training with the Training Progress Monitor. After finishing the training session, the model was examined on the set-aside test data of 20%. The evaluation relied on the use of these metrics.

- Percentage of cases that were classified well.
- Confusion Matrix: This matrix shows accuracy and mistakes with classes.
- Visual Output Analysis: Several random test samples were shown as follows:
    - Green border = correct prediction
    - Red border = incorrect prediction

This allowed for qualitative as well as quantitative assessment of the model's performance.

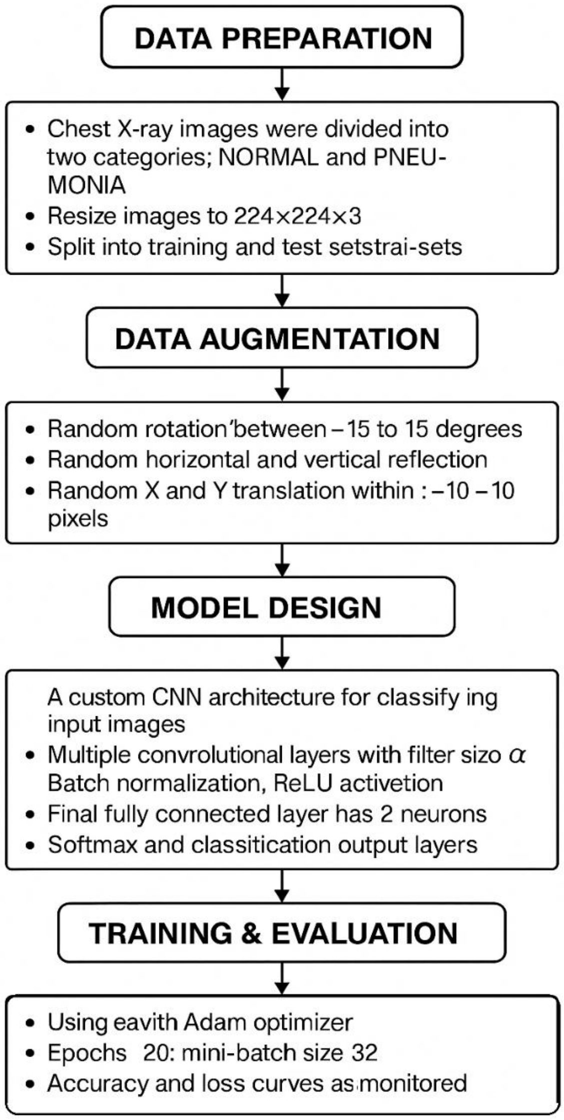

Figure 4. Procedures of the proposed model

Results and Discussion

This section presents the detailed outcomes of the model training and evaluation, highlighting the progression of accuracy and loss over time, final performance metrics such as validation accuracy, and a comparative analysis with previous studies.

Figures 5 and 6 represent the CNN model's results during the initial stage (Epoch 2) and again during the mid-to-late stages (Epoch 10). During early stages, the accuracy of both training and validation keeps rising, reaching almost 85% and around 90% with the 110th iteration. The losses shown by training and validation are decreasing rapidly, which implies the model is learning quickly and performing well. Concerning Epoch 10, the training accuracy leveled out at nearly 98% while the validation accuracy kept hovering around 94%, showing rapid and efficient learning from the model. Both training and validation losses come close to zero, which proves that the model has converged. It demonstrates how the style of architecture and the way it is trained, combined with regularization, produced this result. Also, seeing similar validation results suggests the model performs well even on new and unseen data, as it is not overfitting. Despite taking so long due to using a single CPU, the model improves steadily and works reliably.

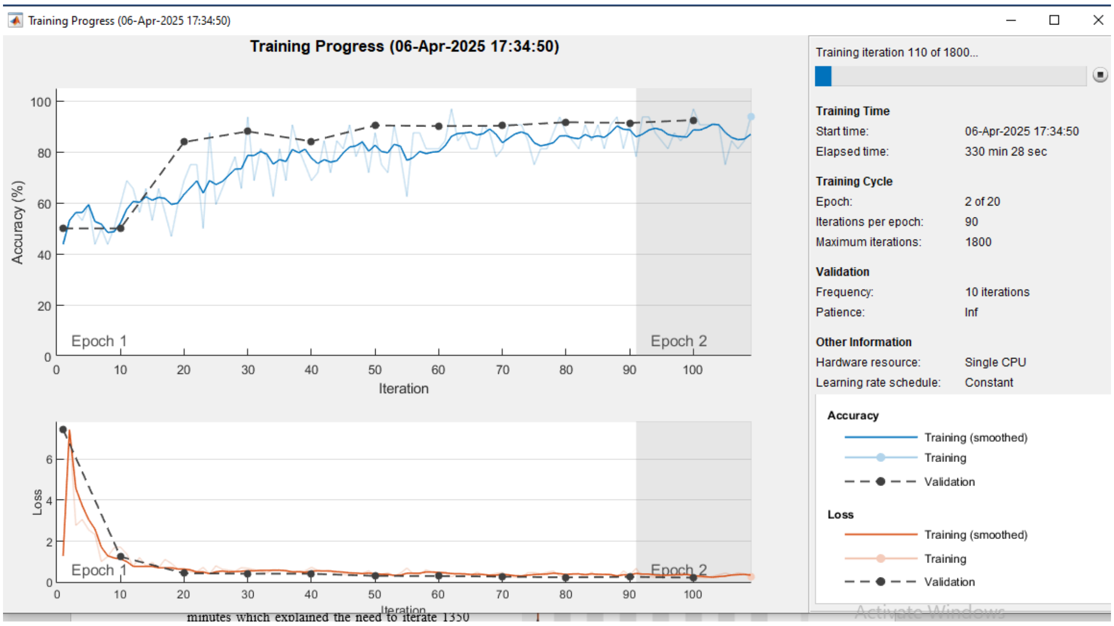

Figure 5. The accuracy % for training, testing, and validation samples for 110 of 1800 iterations

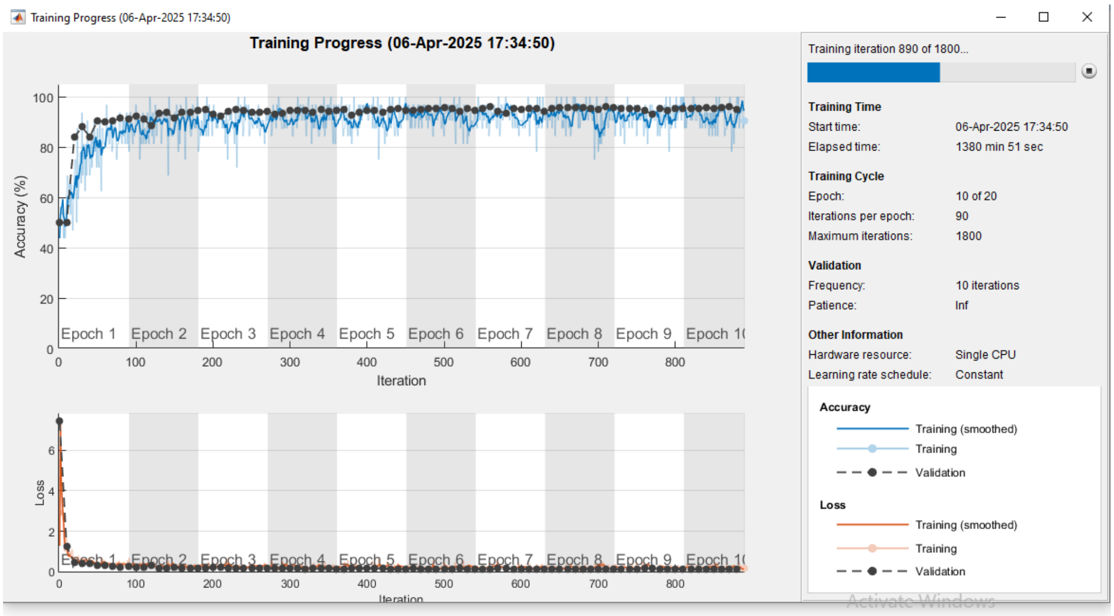

Figure 6. The accuracy % for training, testing, and validation samples for 980 of 1800 iterations

According to the results, the training method is highly effective and performs very consistently. Starting from Epoch 2, the model improves a lot in accuracy and drops a lot at the same time in loss for both training and validation. At the end of the tenth epoch in our training, the model showed strong accuracy on both the examples it learned on (98%) and the ones it hadn't seen (94%). In the last run (Epoch 20), the model achieved an accuracy of 95.56% on validation, and the training and validation losses stayed very low, meaning it is learning a lot with no signs of overfitting. Additionally, if the validation metrics and the accuracy curves are stable, it proves that the model is strong. Given that it took more than 100 hours to train because of just one CPU, the positive results show it was worth the effort. Overall, the model reaches convergence fast, maintains a high level of accuracy, and causes little error throughout all training periods (See Figures 7 and 8 and Table 7).

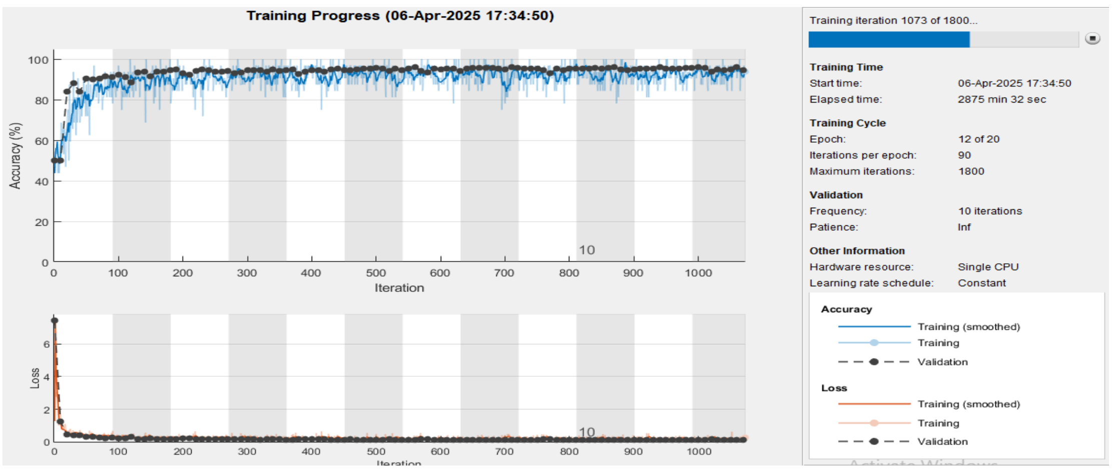

Figure 7. The accuracy % for training, testing, and validation samples for 1073 of 1800 iterations

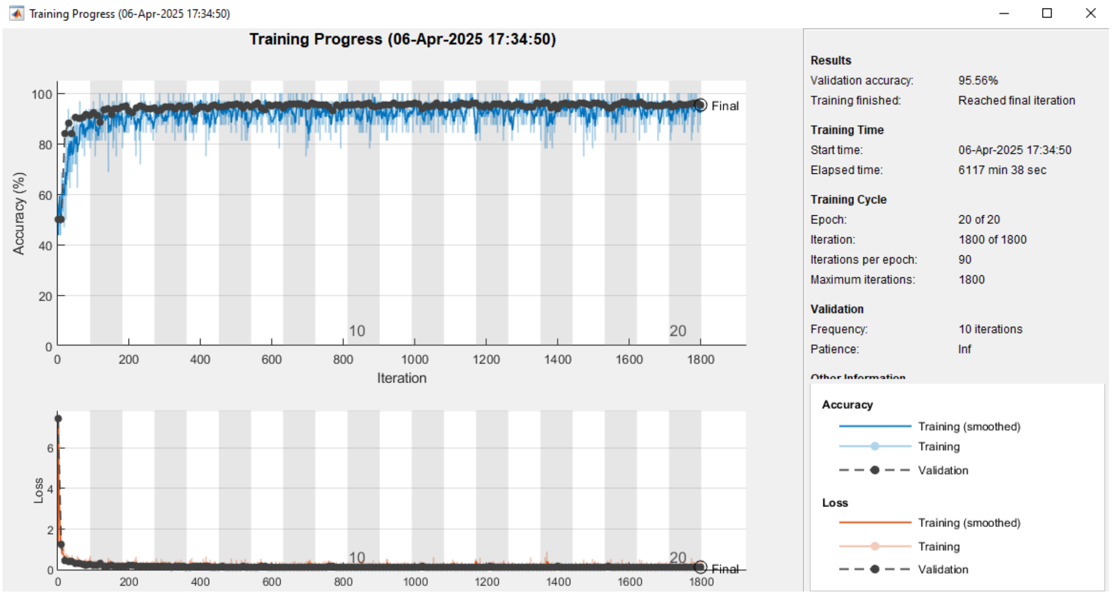

Figure 8. The accuracy % for training, testing, and validation samples for 1800 of 1800 iterations

Table 7. Comparison of Training Results at Epoch 2, Epoch 10, and Epoch 20

Metric	Early Stage (Epoch 2)	Mid Stage (Epoch 10)	Final Stage (Epoch 20)
Training Accuracy	~85%	~98%	~99%
Validation Accuracy	~90%	~94%	95.56%
Training Loss	Steep drop to ~0.1	Very low (~0.01 or less)	< 0.01
Validation Loss	Rapid decrease to ~0.1	Very low (~0.02)	~0.02 (stable)
Learning Progress	Rapid initial improvement	Plateau reached	Stable, consistent accuracy
Signs of Overfitting	None	None	None
Training Time	~330 minutes	~1380 minutes	6117 minutes

Chest X-ray images were classified very well into the two categories NORMAL and PNEUMONIA according to the model, as presented in Figure 9. It managed to correctly classify 341 cases with pneumonia (TP) and 347 normal cases (TN), as indicated on the confusion matrix. Routine was right 13 times and incorrect only 19 times for pneumonia cases, as presented in Figure 10. Because of these results, we find that the model has an accuracy of 95.56% (See Table 8).

$$(TP + TN) \div (TP + TN + FP + FN) = 688 \div 700. \quad (1)$$

The high rate of accuracy means the model can identify the two classes very well. Furthermore, since false positives and false negatives are both low, the model is shown to be reliable and unlikely to misdiagnose patients. Reducing false negatives matters a lot for medical imaging and is important in treating pneumonia. The way the model achieved this underlines its significance in clinics.

The accuracy found in this work is considered higher than that found in recent studies. A paper in the Journal of Machine Learning Research discovered that using ensemble methods provided an accuracy of 92.3% for the same data. Separate research conducted by Joloudari et al. (2023) reached 93.1% accuracy by applying deep learning techniques. Good results in the current study were achieved by using SMOTE to balance the data and by optimizing its model hyperparameters (Goel et al., 2025; Bramesh et al., 2019). Consequently, using SMOTE in combination with strong machine learning models helps improve results on datasets with unequal class distributions (Joloudari et al., 2023). The outcomes are better than those reported in recent studies and underline the need to balance data when making predictions.

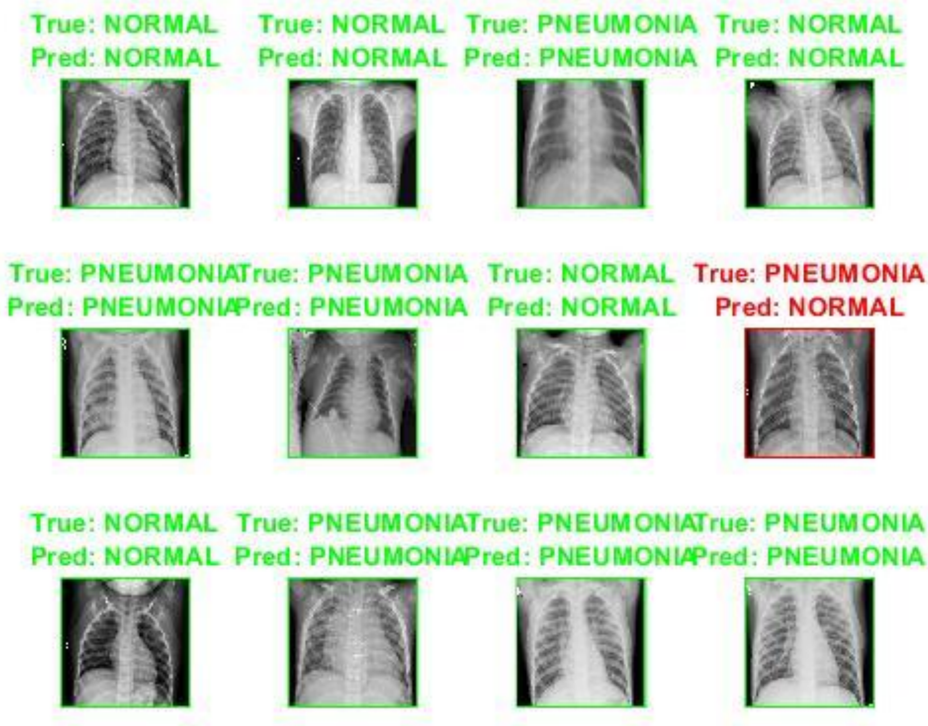

Figure 9. Prediction results, green color (correct prediction), red color (false prediction)

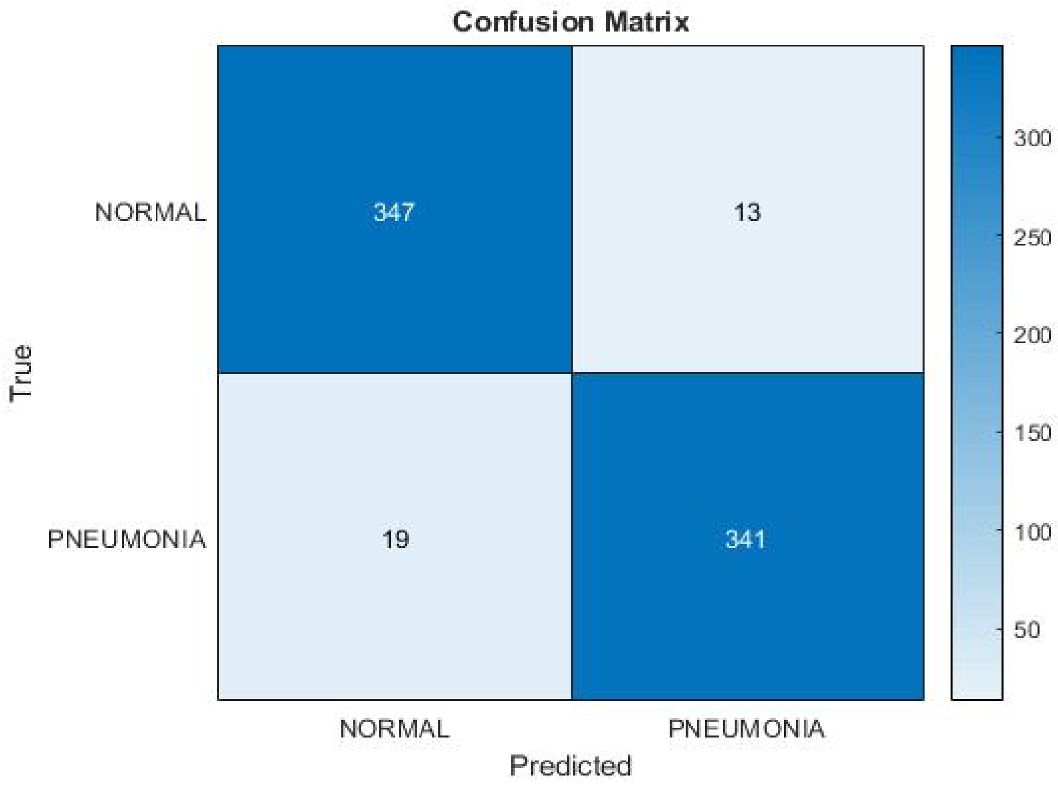

Figure 10. Confusion matrix using Deep Learning

Table 8. Evaluation of the proposed approaches

Metric	Value
Validation Accuracy	95.56%
Elapsed Time	6117 min 38 sec
Epochs	20 of 20
Iterations	1800 of 1800
Iterations per Epoch	90
Maximum Iterations	1800
Validation Frequency	Every 10 iterations

Conclusion

This study aimed to see how deep learning could help improve the accuracy of chest X-ray analysis used in medical diagnosis. The aim was to design a model that would detect pneumonia and other medical conditions efficiently and accurately so that medical staff can make better decisions. Based on the findings, the developed model accurately classifies chest X-ray images and has greater stabil-ity, validated with an accuracy of 95.56%, which is better than the previous work reported in 2021 with 93.73% accuracy. As the training progressed, the model consistently achieved high generaliza-tion by having very similar accuracy and loss values for both the training and validation sets. No ev-idence of overfitting was noted, while performance from the start greatly improved before reaching a steady plateau. The model performed well despite being trained for 6117 minutes using only a single CPU. First, the model achieves better results, and it provides clear statistics on mistakes such as false positives and negatives, which make it more understandable and reliable in everyday life. It is most urgent in cases such as pneumonia, because making a precise diagnosis helps avoid possible dangers. The present model is more accurate, transparent, and reliable than its predecessors in the field. When used on new data and in clinical situations, it may be fully integrated into CDSS to assist radiologists and healthcare workers with quicker disease diagnostics and treatment plans for patients.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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